

(c)  $\hat{\theta}_b := s_{b1}^2 - s_{b2}^2$

(d)  $\hat{\theta}_b := \frac{\bar{x}_{b1}}{\bar{x}_{b2}}$

(e)  $\hat{\theta}_b := \frac{s_{b1}^2}{s_{b2}^2}$

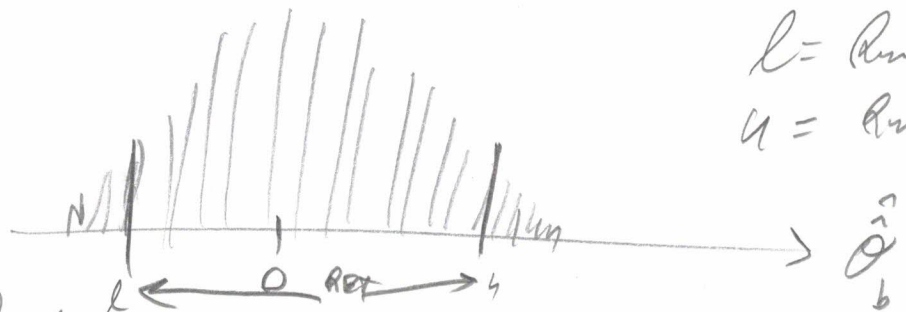
k-S STATISTICS

(f)  $\hat{\theta}_b := d_{b1} - d_{b2}$

If  $n_1 = n_2 = 100$ , then we  $\binom{200}{100} = 10^{50}$  possible subsets.

∴ many more!!!

Now, using the computer, we create  $B$  many, many subsets  $b$  and calculate whichever  $\hat{\theta}_b$  we choose to estimate the statistics. This approximates the null distr.



$l = \text{Quantile}[\hat{\theta}_b, \frac{\alpha}{2}]$   
 $u = \text{Quantile}[\hat{\theta}_b, 1 - \frac{\alpha}{2}]$

Now we order the  $\hat{\theta}_b$ 's and the  $\frac{\alpha}{2}$  and  $1 - \frac{\alpha}{2}$  percentiles form the endpoints of RET. Now we compute  $\hat{\theta}$  in the ACTUAL sample and see

$\hat{\theta} \in \text{RET} \Rightarrow \text{RETAIN } H_0.$

$$\binom{n}{n_1} = \binom{n}{n_2}$$

(2)

This is an exact test if we would simulate all  $n$  samples, otherwise it is approximate. With small sample sizes it is exact. However, if  $N$  is very large, in the millions, it's pretty much exact.

This test is non-parametric as we didn't make any distribution assumptions. The K-S test is also non-parametric.

"Fisher's Permutation Test"

Each  $\hat{\theta}$  definition is a new test!

Why have many tests for the same  $H_0$ ?

Because each test has different power based on the underlying OBP's.

Non-parametric tests tend to have higher power than parametric tests when the parametric tests are highly approximate (see demo).

How to get pval? Expand  $RET_\alpha$  until  $\hat{\theta} \in RET$ .

This is equivalent to  $\min\{2P(\hat{\theta}_b > \hat{\theta}), 2P(\hat{\theta}_b < \hat{\theta})\}$

Ways to get CI's? Yes, beyond scope of course.

Very powerful test: Efron's "Bootstrap". (1979)

Let  $X_1, \dots, X_n \stackrel{iid}{\sim} \text{DBP}(\theta_1, \dots, \theta_k)$

Let  $\phi = g(\theta_1, \dots, \theta_k)$  which could be almost anything

e.g.  $\phi = \text{Med}(X)$ ,  $\phi = Q[X, 25\%]$ , etc.  
 $\Rightarrow \hat{\phi} = \text{Med}[X_1, \dots, X_n]$ ,  $\hat{\phi} = Q[X_1, \dots, X_n, 25\%]$

Generally speaking, we do not know how to get the distr. of  $\hat{\phi}$  so we can get inference.

The bootstrap gives you an asymptotically valid distr of  $\hat{\phi}$ .

Method: for many  $B$  resamplings, draw  $\{X_{b,1}, \dots, X_{b,n}\}$  with replacement from  $\{X_1, \dots, X_n\}$ , the original dataset. Then compute  $\hat{\phi}_b$  for this resampling. Doing this many times,

this gives you  $\approx \frac{2}{3}$  of the original distr. pts.

$\{\hat{\phi}_1, \dots, \hat{\phi}_B\}$  can be thought of as samples from  $\hat{\phi}_{boot,n}$  which is approximately  $\hat{\phi}$  i.e.  $\hat{\phi}_{boot,n} \xrightarrow{d} \hat{\phi}$

"Pull yourself up by the bootstrap" means save yourself miraculously. which is exactly what this is!

How to get CI's?

$$CI_{\hat{\phi}, 1-\alpha} = \left[ Q[\{\hat{\phi}_1, \dots, \hat{\phi}_B\}, \frac{\alpha}{2}], Q[\{\hat{\phi}_1, \dots, \hat{\phi}_B\}, 1 - \frac{\alpha}{2}] \right]$$

How to do testing?  $H_0: \phi \neq \phi_0$

If  $\phi_0 \in CI_{\hat{\phi}, 1-\alpha} \Rightarrow \text{Retain } H_0$

One-sided tests ... make

1-sided CI's (not covered).